Haile quals day 5

Computational models play an important role in cognitive science and in your reading list. It is likely, however, that complex skills, such as computer programming, would also require complex models, and complex models often contain many additional assumptions and parameters, making it easier to explain any type of data. Based on your reading list, how would you make sure that a possible model of computer programming is a realistic account of how humans learn?

Building models and explaining behavior or cognitive dynamics is very much an *art* because intuitive and well-informed guesses have to be made during construction. There are guidelines we can follow, and many computational and statistical tools enable us to hit a "good fit" mark but how realistic an account the model is depends on the theories and observations it exploits. Every model is a good model until a better one comes along that explains the phenomenon better. Therefore, like most other tools, computational models have to provide converging evidence to be deemed most realistic (Daw, 2011).

There are multiple ways one can model a complex task like learning a programming language and difficult choices have to be made. This may be true because: 1) there are numerous models and architectures that could explain the phenomenon, 2) complex skills are multifaceted, some facets of which have not been explained so a choice has to be made about which aspects, or even how many, to model for a reasonably complete model, 3) complex skill learning is represented by cognitive hierarchies where lower-level, simpler learning methods combine to form upper-level, compound strategies and lastly, 4) are the models attempting to explain individual differences, or cortical and subcortical dynamics, or cognitive dynamics, or behavior or all of the above? In other words, modeling complex tasks are difficult and overwhelming (Lee and Anderson, 2001). By no means does this list capture all the complexities involved in such an undertaking, computational models could be very resources intensive (both time and computing power) so some sacrifice in detail or method might be necessary to even have a working, describable model.

As a starting point, the phenomenon of interest will require the use of models that have explained it well in the past. For instance, Collins (2018) used standard reinforcement learning models to explain trade-off between learning mechanisms that occur due to changing task environmental demands. The study sought to compare working memory (WM) and reinforcement learning (RL), and integrate them, so large modifications, with many more parameters (in addition to the standard learning rate), were made to the set of models to capture additional learning behavior and the hallmark behavioral indices of WM function like learning with few trials and fast decay. In a series of studies Collins and colleagues demonstrated the utility of their models with EEG markers and even demonstrated loss of function in disorders (e.g., Collins and Frank, 2018; Collins et al., 2017). Collins and colleagues have forwarded meticulously designed and tested models that fit behavioral data well on their simple stimulus-response learning task and provided converging evidence. But a criticism of the theoretical aspects of their models has necessitated the use of other models (Haile et al., 2020). For instance, the models by Collins and colleagues did not account for competing declarative learning of associations on their simple stimulus-response learning task. Haile et al., 2020 demonstrated that declarative memory models built on the ACT-R cognitive architecture also explained behavior, and additionally tried to capture individual differences. This is just to illustrate that modeling decisions are heavily influenced by their theoretical underpinnings and the study goals.

The first step for any modeling project, for complex skills or otherwise, must clearly state the goals and the scope of the problems it is going to address (Wilson and Collins, 2019). This will be informed by other models that have sought to do something similar, the behavioral task to be modeled and the methods for analyzing the data or fitting models. For example, ACT-R is a well-established cognitive architecture that is one of the most popular architectures to examine learning complex skills, including programming. Therefore, models based on ACT-R would probably be the most useful to understand programming learning.

Developing theoretically sound models also requiring setting clear goals for them. Are the models supposed to test different hypotheses for how learning might occur? Will they be used to estimate stable latent variables to explain cognitive dynamics? Our choices for constructing the models, comparing the model data to behavioral data, and testing or computing parameters will be greatly affected by the goal. Clearly defining the goal goes a long way towards building realistic models.

The next vital point is selecting methods for model fitting, arbitrating models, and interpreting the results. There are very few hard and fast rules here. It seems like most researchers follow best practices in their fields and lots of logical reasoning to carry out these necessary steps and make sure methods are transparent and do not over-emphasize findings. For instance, Wilson and Collins (2019) have compiled a list of ten simple rules that cognitive modelers use to build, analyze, and present their models.

Computational models are powerful tools but just like all others used in research it is vital to use transparent research practices, not over-emphasize results, use appropriate tools to arbitrate model fit and provide converging evidence from multiple methods.